

MOTOR VEHICLE USAGE PATTERNS IN AUSTRALIA: A COMPARATIVE ANALYSIS OF DRIVER, VEHICLE & PURPOSE CHARACTERISTICS FOR HOUSEHOLD & FREIGHT TRAVEL

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An ordered probit model is used to predict motor vehicle usage in Australia on the basis of the unit record files underlying the Australian Bureau of Statistics' Survey of Motor Vehicle Use. Both household and freight transport are analysed. The paper examines the statistical significance of a number of driver, vehicle and travel purpose variables on the level of motor vehicle usage. Factors analysed include driver age and gender, vehicle and fuel type, age of the vehicle, purpose of trip, place of registration, type of freight and number of drivers. The results indicate that the cut-off points between very low, low, medium, high and very high vehicle usages are significant and that the factors associated with differences in usage include driver age, engine size and age of vehicle for household vehicles and the type of freight, type of vehicle, gender and number of drivers for freight usage.

KEY WORDS: Motor vehicle usage, driver, vehicle and purpose characteristics, ordered probit.

JEL CLASSIFICATION: D12, C21, C25, L92.

I. INTRODUCTION

Road transport plays a major role in Australia's economy and society. And fundamental to the provision of road transport is the usage of motor vehicles. Households use their vehicles for access to their places of work, education and recreation, while the use of vehicles by business is primarily for the movement of goods and the provision of services. However, and seemingly regardless of the now century long dominance of motor vehicles on Australian roads, motor vehicle usage continues to attract a significant amount of empirical attention by Commonwealth and state government departments, transport organisations, industry groups and academic researchers aimed at setting and implementing transport policy and determining road funding and investment. Justification for this ongoing interest is not hard to find, especially when in a country of Australia's size road transport will continue to play a significant role in the efficient functioning of the economy for at least the foreseeable future.

Currently, the movement of people and goods by road in Australia takes place on more than 811,000 kilometres of road, with 84.4 percent of the network comprising local roads and 40 percent featuring a sealed surface (Austroads, 2000). The vastness of this road network is especially apparent in terms of the number of persons per kilometre of road, such that in Australia there are approximately 24 persons per kilometre of road, less than half the number found in comparable economies such as the United States and New Zealand (Austroads, 2000). Australia's road infrastructure is currently valued in excess of \$100 billion and requires significant ongoing building and maintenance expenditure by all levels of government and the private sector. For instance, in 2000-01 construction activity undertaken by public

and private organisations for the construction of roads, highways and bridges totalled \$1.8 billion and \$3.8 billion respectively (ABS, 2001d).

In the year to October 2000 the total kilometres travelled by all vehicles in Australia was estimated at 180.8 billion kilometres (ABS, 2001a). While this represents only a slight increase from previous years, increasing amounts of road usage are concentrated on a smaller proportion of the road network. For example, while nearly 85 percent of the network constitutes local roads, these roads carry less than 25 percent of all traffic, with the remaining network comprising rural and urban arterial roads and national highways (Austroads, 2000). Likewise, within each state more than half of the average distance travelled per year occurs in the capital cities, as opposed to the provincial cities and non-urban areas (ABS, 2001a). And while the proportion of kilometres travelled for personal use has declined marginally over the last 20 years (from 48.9 percent in 1979 to 43.5 percent in 2000), the share of business travel has increased (from 32.2 percent in 1979 to 34.4 percent in 2000) as well as travel to and from work (from 18.8 percent in 1979 to 22.1 percent in 2000) (Austroads, 2000; ABS 2001a).

The road network also plays a major role in freight transport. In 2000-01, freight movements by road accounted for 52.4 percent of the 1.2 billion tonnes of domestic freight uplifted, as compared to 43.5 percent for rail, 4 percent for sea and 0.01 percent for air (ABS, 2002a). However, since road freight transports high tonnages over relatively short distances, road's share of total tonne-kilometres (mass moved over distance) is 29 percent when compared with 39 percent for rail and 32 percent for sea (ABS, 2002a). While road transport obviously represents a significant proportion of business costs, the cost of household road transport is also significant. In fact, private consumer transport expenditure represents some 16.9 percent of the household budget and comes second only to the proportion spent on food (ABS, 2000). Of this transport expenditure, the majority (73.7 percent) is spent on private motoring with the remainder on public transport (ABS, 2000). For example, the NRMA (1999) estimated that a medium sized car that is from new to 3 years old, travels approximately 15,000 kilometres per year, and was bought on a personal loan for 75% of the purchase price at an interest rate of 10.2% over four years costs the owner approximately \$174.70 per week, excluding running and maintenance costs.

Due to the high volume of transport services used in Australia, the transport industry itself contributes a significant percentage to overall economic activity. In 2000-01 the transport and storage industry was worth \$31.6 billion, contributing 5.0 percent to total gross domestic product (GDP). Of the transport and storage industry's contribution to GDP, the road transport sector accounted for 30 percent in this same period (ABS 2001c). In addition to representing a sizeable proportion of economic output, the industry currently employs approximately 4.4 percent of Australia's labour force with over half of these jobs generated by the road transport sector (ABS 2002b). Significant amounts of turnover and employment are also accounted for by particular industries within this sector. For example, in 1999-00 turnover in operating buses for the transportation of passengers in urban areas and over long distances was estimated at \$2.9 billion, with a labour force of nearly 35,000 people; operators of taxi cabs and hire cars generated turnover of \$1.2 billion and employed over 10,000 people; the manufacturing of motor vehicles generated turnover of \$13.1 billion, with a labour force of 15,693 people; motor vehicle retailing generated turnover of \$21.9 billion and employed some 35,000 people; and firms engaged in retailing automotive fuel or lubricating oils provided turnover of \$17.2 billion with the industry employing approximately 42,000 people.

Of course a number of externalities also arise from motor vehicle usage including, pollution, congestion, and road traffic accidents, as well as the transport planning activities undertaken by government departments and transport organisations through the collection of road revenue and the infrastructure investment decisions and road expenditure undertaken. In terms of air pollution the Australian Greenhouse Office (AGO, 2001) estimated that Australia's transport sector produced 16.1 percent of total CO₂ equivalent emissions in 1999, with 90.2 percent of emissions produced by road transport, cars being the major contributor. Noise pollution and congestion are yet other problems associated with road transport that can have a number of effects on health and well-being (Button, 1994). Lastly, road accidents are a widely recognised undesirable consequence of road transport and include the costs

associated with deaths, injuries and damage to vehicles; currently estimated to cost \$15 billion per annum (Austroads, 2000).

Lastly, in order to build and maintain the largely publicly provided road transport network, as well as managing the externalities associated with its use, Commonwealth and state governments use the revenue collected from a number of taxes and charges levied on road users. In 1997-98 a total of \$13.7 billion in revenue was generated by motor vehicle taxes, charges and fees for the Commonwealth and State governments (Austroads, 2000). For instance, the purchase of a new vehicle attracts a goods and services tax (GST) valued at 10 percent of the vehicle purchase price, a luxury car tax of 25 percent for vehicles over \$55,000, vehicle ownership costs include annual registration charges, compulsory third party insurance, stamp duty (applicable on initial car registration, transfer of ownership and insurance), driver's licence, and other charges specific to each State or Territory (Austroads, 2000). In terms of vehicle use, the Commonwealth levies an excise on leaded and unleaded petrol and diesel, toll charges are applicable on some roads in certain states. However, though road transport related revenue is indeed significant, only some fifty percent is currently outlayed by all levels of government directly for road related expenditure (Austroads, 2000).

With these statistics in mind, the modelling of road transport usage can make an important contribution to understanding both the patterns of motor vehicle activity and the evaluation of policy, planning and operational initiatives aimed at improving efficiency and reducing negative impacts associated with road transport (D'Este, 2000). The purpose of the present paper is to investigate the role of driver, vehicle and usage characteristics in determining this pattern of motor vehicle usage. The paper itself is divided into four main parts. The first section provides a brief empirical survey of travel demand and vehicle usage models. The second section discusses the methodology and data to be employed in the paper. The results of the analysis are examined in the third section. The paper ends with some brief concluding remarks.

II. EMPIRICAL SURVEY

(i) Aggregate and disaggregate travel demand models

The empirical literature on motor vehicle usage lies within the broader field of transport demand modelling. Two main forms are recognised. First, aggregate travel demand models aim to represent the behaviour of a group of travellers through the estimation of aggregated data. Though initially developed in response to the realisation that travel choices are rarely identified separately (Hensher and Goodwin, 1979), these techniques have also been used for aggregating individual travel behaviour using micro-data [see, for example, McFadden et al. (1977), Stubbs *et al.* (1980), de Dios Ortuzar and Willumsen (1994) and Train (2002)]. Aggregate demand functions can be further categorised as consistent or approximate, depending on the method used for estimation. The first type of aggregate demand is obtained by summing individual demand functions and is therefore considered to be most consistent with underlying demand. However, this type of demand function is difficult to estimate and is not widely employed (Train, 1986). The second, and more common, type of demand function are those that approximate the underlying aggregate function, but are not necessarily consistent with notions of realistic individual demand (Train, 1986).

Second, disaggregate travel demand models focus instead on the choices of whether a travel journey should be undertaken in the first instance and by which transport mode in the second. Past research has examined a number of travel choice problems including the choice of destination, time of day to travel, level and type of car ownership, degree of vehicle usage and duration of vehicle ownership. Such models are generally regarded as the most appropriate for examining travel choice problems since these decisions are ultimately based on behavioural observations of individuals or households and theories of consumer choice and utility maximisation (Bitzios and Ferreira, 1997: 11). Within disaggregate travel choice models, three broad characteristics exist that further categorise this approach. These are (i) real or

hypothetical choice models, (ii) discrete or continuous choice models, and (iii) static or dynamic choice models.

The first, real (or revealed-preference) or hypothetical (or stated-preference) choice models, depends on whether the household's choice of travel is observed in a real situation or whether the household is asked what it would do in a hypothetical situation (Train, 1986). Of these, revealed-preference models are the common approach taken in modelling current transport usage patterns, whereas stated-preference models are associated with transport choices consumers have yet to experience (such as the demand for electric vehicles). The second types of disaggregate transport choice models relate to either discrete or continuous choice. Discrete choice relate to one-off decisions regarding transport (such as the level and type of vehicle ownership), whereas continuous choice refers to decisions made on an ongoing basis (such as vehicle utilisation). The third type of model is made on the basis of whether it contains static or dynamic elements. This is primarily related to the household vehicle ownership decision, since in the long run the vehicle ownership process is essentially dynamic, with static models focusing on a one off travel decision.

Empirical studies involving the estimation of vehicle usage can be dated back to at least the mid 1960s where an aggregate model was estimated as a means of forecasting car ownership and use (Kain and Beesley, 1965). However, interest in vehicle utilisation models, especially disaggregate models, gained attention in the 1980s due to increased concerns for energy availability and fuel consumption emerging from the energy shocks of the 1970s (Mannering, 1983; Greene and Hu, 1984; Mannering and Winston, 1985; Hensher, 1985a). In the 1990s interest in household vehicle usage was renewed, this time as a result of interest in forecasting vehicle emissions and the demand for alternative-fuel and environmentally friendly vehicles (Golob *et al.*, 1996; Golob *et al.*, 1997; Bjorner, 1999). Past modelling of vehicle utilisation within these areas can be divided into three areas: (i) joint (continuous/discrete) decision models; (ii) vehicle utilisation within multi-vehicle households; and (iii) aggregate estimates of total distance travelled by passenger vehicles.

(ii) Joint decision models

Early travel demand models estimating the decisions of the number, type and vintage of vehicles generally failed to recognise the importance of the effect distance travelled by the household has on these transport decisions. That is, a household's motor vehicle usage may impact upon its decision in regard to the number of vehicles owned. A vehicle's fuel efficiency, which in turn is related to driving habits, may also influence the type of vehicle owned, and conversely the number and type of vehicles a household owns affects the frequency and distance the household members drive and hence the amount of fuel consumed (Mannering and Train, 1985). Many early studies either ignored the vehicle miles/kilometres travelled (VMT/VKT) or assumed it to be exogenous (Mannering and Train, 1985). An obvious alternative was the specification of joint decision models, including those undertaken by Train and Lohrer (1983) and later Mannering and Winston (1985).

Using US household data, Train and Lohrer (1983) specified seven sub-models containing decisions regarding the number of vehicles to own (restricted to two vehicles), the class and vintage of each vehicle, the miles travelled in each vehicle (VMT) and the proportion of VMT by category of travel trip. Importantly, while these sub-models were estimated sequentially, this was not assumed to be the actual sequence in which households make these decisions. By comparison, Mannering and Winston's (1985) joint decision model took into account the dynamic elements of automobile demand. The data utilised was collected over three periods, capturing purchasing and utilisation behaviour before, during and after the June 1979 energy shock (Mannering and Winston, 1985). Similar to Train and Lohrer (1983), separate models were estimated for one and two vehicle households based on the choice of vehicle quantity, type and utilisation.

A later study by Hensher *et al.* (1990) used Australian multi-vehicle household data collected from the Sydney metropolitan area during 1981/82. In contrast to Train and Lohrer (1983) and Mannering and Winston (1985), Hensher *et al.* (1990) specified a vehicle utilisation model that simultaneously considered vehicle type and usage choices. For households with two or more vehicles the model treated

each vehicle as a unique entity, similar to the earlier approach taken by Train and Lohrer (1983) and Mannering and Winston (1985). Hensher *et al* extended their study to estimate separate usage equations for households with 1, 2, 3 and 4 or more vehicles (Hensher *et al.*, 1990). Despite several key differences, all three studies specified an array of household socio-economic, financial and locational variables as well as vehicle specific variables as determinants of vehicle usage. For example, for two vehicle households all three studies included a dummy variable indicating if the observational vehicle was the newer vehicle. Both Mannering and Winston (1985) and Hensher *et al.* (1990) concluded that households drive their newer vehicles more than the older vehicle.

And in most other respects, the results of these three studies are comparable regarding the specification of the explanatory variables and the relationships between these and the level of household vehicle ownership. For instance, Train and Lohrer, (1983), Mannering and Winston (1985) and Hensher *et al.* (1990) all concluded that vehicle ownership was positively related to income, while household size (Train and Lohrer, 1983), the number of workers (Train and Lohrer, 1983; Mannering and Winston, 1985) and the expected number of miles/kilometres driven annually were also significantly positive. Conversely, operating costs (Train and Lohrer, 1983; Mannering and Winston, 1985 and Hensher *et al.* 1990), the age of the household head or primary driver (Mannering and Winston, 1985 and Hensher *et al.*, 1990) and vehicle age (Hensher *et al.*, 1990) all lead to a decrease in household vehicle use. Other results included Train and Lohrer's (1983) finding that households in large urban areas drive more than households in small urban areas, and those in small urban areas drive more than households in rural areas.

De Jong (1990), Linciano (1997) and Bjorner (1999) have also undertaken work in this area. Both de Jong (1990) and Bjorner (1999) used maximum likelihood methods to simultaneously model vehicle ownership and vehicle usage, taking account of both fixed and variable costs based on datasets from Holland and Denmark respectively. Linciano (1997) studied the vehicle usage decision conditional on vehicle ownership in the U.K., accounting for self-selectivity through the application of a probit model at the discrete choice stage and least squares estimation for the continuous choice, together referred to as the Heckman model. The results of these studies generally supported Train and Lohrer, (1983), Mannering and Winston (1985) and Hensher *et al.* (1990), while de Jong (1990) and Bjorner (1999) also concluded that a female driver or household head was associated with lower vehicle usage.

Other developments in joint decision models have extended the estimation of joint decisions beyond vehicle ownership, type choice and usage. For example, Schimek (1996) estimated a model that studied the relationship between choice of residence, automobile ownership and automobile usage. The estimated model produced similar inferences to those of previous studies for the explanatory variables of income, household size, number of workers and driver age, and in addition found that an increase in population density would decrease the level of vehicle travel per household each year. Similarly, de Jong (1996) estimated decision models of vehicle holding duration, vehicle type choice and annual travel length, for Dutch households with initially one vehicle. The estimated parameters again supported comparable studies and also suggested that highly educated persons drove more kilometres.

(iii) Vehicle usage in multi-vehicle households

Research on how multi-vehicle households utilise each of their vehicles became popular amongst transport economists at the same time as joint estimation techniques. Mannering and Train (1985: 268) identify two interrelated concerns that form the reasoning behind modelling vehicle usage in multi-vehicle households. These are: "...(i) how to capture the process by which households assign vehicles to trip-generating activities, and (ii) how to account for the fact that household vehicles can be used as substitutes". Mannering and Train (1985) argued in the first instance that the vehicle assignment process needed to consider the compatibility of vehicle attributes with household activities; that is, how vehicles are assigned for use between household members and the occurrence of individual vehicle ownership in the household. These same issues would also be addressed when considering the concept of vehicle substitutability in the second instance. It is interesting to note that while a number of joint decision studies also examined vehicle usage in multi-vehicle households, none of these explicitly addressed the

issue of vehicle substitutability as relevant to multi-vehicle household usage models (Mannering and Train 1985).

Two early studies in vehicle usage in multi-vehicle households were by Mannering (1983) and Hensher (1985a). Mannering (1983) constructed a simultaneous equation system for two vehicle households that incorporated the occurrence of substitution across vehicles. Two models were estimated, one for each vehicle in the household, using a three-stage least squares simultaneous equation procedure. The data set applied was based on a three-month period, consisting of relatively few household socioeconomic and vehicle specific variables. However, due to the relatively short time period, Mannering (1983) was able to treat vehicle type attributes as exogenous as it was assumed that the possibility of changing vehicles during this time was unrealistic. Rather, if usage was to be considered over the long-term (i.e. a year) then vehicle type attributes would need to be viewed as endogenous which would necessitate the estimation of type and level choices jointly using discrete/continuous econometric techniques (Mannering, 1983).

Mannering (1983) also highlighted the importance of the principal driver age variable suggesting that attributes of the principal driver provide a clearer indication of likely activity choices in which the vehicle is to be used and also accounts for some of the driver/vehicle associations thought to exist. Hensher's (1985a) study on the influences on household vehicle use were based on a similar assumption in that the interdependence of vehicle use in a household was also assumed to be endogenous. Each vehicle was identified separately in the household observational unit and simultaneous equations were estimated using three-stage least squares. The over-riding difference between the two studies is that Mannering's (1983) study was limited to two vehicle households in the short-run, whereas Hensher (1985a) extended his study to include up to three vehicle households over both the short-run and a 12-month longer-run period. This same data set was later used in a joint decision study by Hensher *et al.* (1990), which took into account substitution between household vehicles.

During the mid-to-late 1990s, vehicle usage research changed focus. Increasing emphasis was now placed on the environmental effects of vehicle emissions, which lead to a renewed interest in the need to forecast vehicle miles/kilometres travelled. Golob *et al.* (1996) and Golob *et al.* (1997) undertook studies in this respect where usage was considered a function of household characteristics, principal driver characteristics and characteristics of the vehicle. Principal driver characteristics specified included driver age, gender and employment status. However, Golob *et al.*, (1997) also included information on consumers' preferences for alternative-fuel vehicles, based on stated preference data, to obtain an idea of the extent to which households would use these environmentally friendlier vehicles over more conventional vehicles. Golob *et al.* (1996) and Golob *et al.* (1997) found that the age of both the first and second vehicles had a negative influence on VMT of each vehicle and on the other vehicle. In terms of vehicle types, it was found that vehicles with greater than average use included subcompact cars, sports cars, full-size vans, compact sport utilities and full-size sport utilities (both first and second vehicles), compact cars and small (compact) pickup trucks (second vehicle only). Mini cars and full-size (standard) cars were estimated to have average usage levels and vehicles with lower than average use included full-size (standard) pickup trucks and minivans (both first and second vehicles), small (compact) pickup trucks (first vehicle only) and mid-size cars (second vehicle only).

Golob *et al.* (1996) and Golob *et al.* (1997) also examined the impact of a number of household characteristics on VMT. Vehicle miles travelled was found to be also positively related to: (i) the number of household members between 16 and 20 years old, (ii) the total number of children, (iii) high-income households, (iv) households headed by younger persons and (v) the number of workers in the household. Further, positive effects on VMT came from the number of children in the household aged 1 to 5 years, however this was for the second vehicle only. Lower household vehicle usage was associated with the number of drivers in the household, retired households (both vehicles) and the presence of three or more household vehicles (second vehicle only). The negative influence of the number of drivers in the household was explained by both studies as indicating a shift of use towards third or fourth vehicles in the household.

(iv) Aggregate household vehicle usage models

Aggregate models examining vehicle usage also date back to the mid-1960s (Kain and Beesley, 1965). However, studies treating vehicle usage as the endogenous variable remained a fairly untouched area of transport modelling until the rise in popularity of the disaggregate models in the 1980s. Rather, the earlier aggregate models required vehicle usage data as a means of estimating fuel consumption, instead of analysing the determinants of vehicle usage (Mannering, 1983; Hensher, 1985a; Hensher *et al.* 1990). Two recent aggregate vehicle usage studies include Walls (1998) and BTE (1998b). The study by Walls (1998) was motivated by the need to model usage of the existing fleet of cars in Hong Kong as an input to an overall congestion abatement strategy. With this in mind, VKT per automobile was posited to be a function of vehicle taxes, vehicle fees, petrol price, income and population. Least squares estimates indicated that vehicle taxes, vehicle fees and petrol prices were expenses directly related to the ownership and operation of the vehicle.

By comparison, BTE (1998b) modelled vehicle usage that took into account distance travelled in capital cities and major provincial urban areas in Australia. City dummy variables were included to reflect the different levels of availability of public transport and/or differences in the propensity to travel by car within these regions (BTE, 1998b). The only other variable included in the model was implied VKT, measured as the product of trends in cars per thousand persons nationally, VKT per car nationally and the population of each city. Pooled time series, cross-section data and estimates using OLS and GLS provided negative values in Sydney, Melbourne and Brisbane, on which basis BTE (1998b) suggested the presence of factors such as high congestion levels and/or higher availability of public transport produced lower urban passenger vehicle VKT. BTE (1998b) predicted that passenger vehicle VKT in capital cities was expected to grow by 1.2 percent per annum from 1995 to 2020, compared to the observed growth rate of 3.5 percent from 1971 to 1995, with the difference assumed to be partly due to slower economic growth and increased saturation of car ownership.

(v) Freight vehicle usage models

Freight vehicles serve a very different purpose to passenger vehicles, as they are primarily associated with the movement of goods rather than people. Modelling freight demand and the movements of these types of vehicles can provide insights into the issues of traffic congestion, distribution patterns and routing, supply chain operations, and pricing and regulatory matters (D'Este, 2000). While the literature on freight demand modelling, both aggregate and disaggregate, is generally less extensive than passenger demand modelling, the topic has been of interest since about the mid 1970s, and formed the basis of a number of literature reviews [see, for example, Winston (1983) and Zlatoper and Austrian (1989)]. Two obvious problems with freight demand modelling studies identified by these surveys are the complexity in the pattern of freight movements and the problems associated with data collection, especially at the disaggregate level.

Many of the techniques that have been applied to modelling freight transport have their origin in methods originally developed for passenger vehicles (D'Este, 2000). Consequently, the intended purpose for estimating road freight models are in some instances similar to passenger vehicles (i.e. mode choice) and in other cases very different (i.e. inventory analysis, firm profit, effects of regulatory change, etc.). And demand for freight movement models are usually estimated in terms of volume (tonnage), number of consignments or as direct vehicle trips rather than distance travelled (D'Este, 2000). However, a number of studies have incorporated road freight tonne-kilometre by commodity to estimate the energy use of road freight vehicles (Vanek and Campbell, 1999; Vanek and Morlok, 2000).

De Dios Ortuzar and Willumsen (1994) found that the majority of freight demand models are of the aggregate form. In part, this can be attributed to their usefulness in estimating freight flows on a large-scale (regional or national) for policy analysis or practical prediction (Winston, 1983) primarily for the purposes of examining modal choice (Winston, 1983; Zlatoper and Austrian, 1989). One such aggregate modal choice model is the basic modal split model where modal share is dependent on the price and service differences between carriers. Another aggregate modal choice model developed in response to shortcomings of the aggregate modal split models by specifying the firm's cost function to derive the

aggregate share of a mode by commodity group and by geographical region (Winston, 1983). However, de Dios Ortuzar and Willumsen (1994) and Winston (1983) recognised that both of these models had a drawback in that while aggregate models were able to provide insights into mode choice, at high levels of aggregation information on the process by which firms optimise their behaviour was lost.

Similarly to passenger demand modelling, the estimation of freight demand by disaggregate methods has proven beneficial in capturing the characteristics of freight demand at the firm level. A literature review Winston's (1983) identified two main types of disaggregate freight demand models, namely, behavioural and inventory. Winston (1983; 421-422) concluded: [B]ehavioural models attempt to focus on the mode choice decisions made by the physical distribution manager of the receiving or shipping form. The analysis is motivated by the proposition that the manager is concerned with maximising the utility, with respect to expense and service, he receives from using a given mode. ...inventory models have attempted to analyse freight demand from the perspective of an inventory manager, [that is] it implicitly attempts to integrate the mode choice and production decisions made by a firm. While inventory models have similar estimation methods to the joint choice models of passenger demand, Winston (1983) and later Zlatoper and Austrian (1989) highlighted the fact that conventional single choice models are theoretically less complete and more likely to be biased than the freight models that jointly analyse important endogenous choices.

As with passenger vehicle studies, freight vehicle research in recent years has focused on the estimation of vehicle emissions and energy use. For example, Vanek and Campbell (1999) and Vanek and Morlok (2000) studied the road freight industry's level of energy use from a commodity-based, rather than a traditional mode-based, perspective. In order to identify which industry sectors have the highest product-specific road freight energy intensity, both studies used information on road freight tonne-kilometre and average energy use per tonne-kilometre. Vanek and Morlok (2000: 21) outlined the importance of this type of study, concluding "...firms defined by a commodity group can use this information to understand their sector's contribution to freight energy use and, where the energy level is determined to be relatively high, set goals for reducing it". Vanek and Campbell (1999) likewise found that the food and drink sector was the largest consumer of road freight energy, followed by manufactured articles, building supplies and agriculture. Vanek and Morlok's (2000) results analysed road freight energy intensity in comparison to the energy used in the production process for that commodity. They showed that foods and kindred products, lumber and wood products, and apparel had the largest transportation energy use components as compared with the energy used in the production process.

III. DATA AND MODEL ESTIMATION

The analytical technique employed in the present study is to specify motor vehicle usage (both household and freight) as the dependent variable (y) in a regression with driver characteristics, vehicle attributes and purpose factors as explanatory variables (x). A large number of vehicle usage studies have employed limited dependent variable or discrete choice models for this purpose. Train and Lohrer (1983), Mannering and Winston (1985), Hensher *et al.* (1990) and de Jong (1996), for example, used logit for analysing fleet size and vehicle type choices. Likewise, Linciano (1997) specified a probit model for the discrete choice of car ownership with the application of least squares for the continuous vehicle usage data, while Bjorner (1999) used the tobit model in his estimation of the discrete/continuous choice of ownership and usage. Winston (1981a) used probit models to examine the demand for intercity freight transportation, and de Palma and Rochat (1997) employed a similar model to examine the impact of weather conditions on the travel decision. Accordingly, the following multinomial ordered probit model with simple heteroskedasticity is specified:

$$\begin{aligned}
y_i^* &= \beta_*' x_i + \varepsilon_i, \\
\varepsilon_i &\sim N[0, w_i], \\
y_i &= 0 \text{ if } y_i^* \leq \mu_0, \\
&= 1 \text{ if } \mu_0 < y_i^* \leq \mu_1, \\
&= 2 \text{ if } \mu_1 < y_i^* \leq \mu_2, \\
&\dots \\
&= J \text{ if } y_i^* \leq \mu_{J-1}.
\end{aligned} \tag{1}$$

where ε_i is distributed normally with a mean of zero and $\text{Var}(\varepsilon_i)$ equals w_i^2 . This model comprises a form of censoring. The μ s are unknown parameters to be estimated with β . The coefficients imputed by the multinomial ordered probit provide inferences about the effects of the explanatory variables on the probability of the possible outcomes for vehicle usage.

All data used in the study is from the previously unreleased unit record files underlying the Australian Bureau of Statistics Survey of Motor Vehicle Use. This survey collects data on passenger and freight vehicle usage where the unit of observation is the vehicle itself. Other information collected includes characteristics of the principal driver, the vehicle, usage patterns and for freight vehicles, the types of commodities carried. Data on passenger and freight vehicle movements collected over the 13-week period from 1 May to 31 July 2000 is specified and contains details relating to 752 passenger and 1,896 freight vehicles.

<TABLE 1 HERE>

The dependent variable in both the passenger and freight vehicle analysis is vehicle kilometres travelled (*VKT*). Vehicles in the sample are categorised into quintiles on the basis of the reported distance travelled: namely, very low, low, medium, high and very high. The lower and upper bound of distances travelled for passenger and freight vehicles in each quintile are detailed in Table 1. For example, the medium level of usage for passenger vehicles is between 2,119 and 3,631 kilometres, while the medium usage for freight vehicles is between 4,415 and 8,432 kilometres.

Three sets of explanatory variables are used to predict passenger and freight vehicle usage. These are: (i) driver characteristics, (ii) vehicle attributes, and (iii) purpose factors. Selected descriptive statistics are presented in Table 2. The first set of characteristics for both passenger and freight vehicle usage relate to driver characteristics. Within a behavioural travel demand model it is expected that the characteristics of the principal driver will have a significant influence on distances travelled. Mannering (1983), for example, argues that older drivers and women tend to select frequencies and types of activities that require less travel. Negative signs are hypothesised when vehicle usage is regressed against driver age (*AGE*) and gender (*SEX*) where the control variable for dummy variable is male. The number of vehicle drivers (*HSE*) is included to take account of the increasing scale of usage for each vehicle and in part proxies household size (Greene and Hu, 1984; Golob *et al.* 1996; Golob *et al.*, 1997). In addition, as part of the driver characteristics for both the passenger and freight analyses, information on the state of vehicle registration serves to act as a proxy for residential or business location. Five dummy variables are specified with NSW as the control: Victoria (VIC), Queensland (QLD), Western Australia (WA), South Australia (SA) and other States and Territories (OTH) including the Northern Territory, Australian Capital Territory and Tasmania). Hypotheses could, of course, be made for each of the States or Territories with the level of usage related to say, land area or road length. Nevertheless, no particular *a priori* sign is hypothesised when vehicle usage is regressed against state/territory of registration.

<TABLE 2 HERE>

Of course, there are a large number of other driver characteristics that could have been included in the analysis had the data set employed focused on the user rather than the vehicle. For example, Mannering (1983), Green and Hu (1984), Hensher (1985), Golob *et al.* (1996), and Linciano (1997) all included household income with the hypothesis that road transport as a normal good would be higher in high-income households. However, the evidence supporting this is mixed, with Golob *et al.* (1996) and Linciano (1997) regarding income as an important influence on vehicle usage, and Green and Hu (1984), Hensher (1985) and Hensher *et al.* (1990) concluding otherwise. Another driver/household characteristic included in past studies is geographical location, primarily delineated as urban or rural [see, for example, Train and Lohrer (1983), Mannering and Winston (1985), Linciano (1997) and Bjorner (1999)]. The underlying hypothesis in this respect is that the lower population density of rural areas, the distances to services, facilities, places of work and education, and the lack of public transport are associated with higher vehicle usage.

The second set of characteristics specified as explanatory variables relate to the attributes of the vehicle itself. Vehicle attributes posited to have a relationship with vehicle usage in past studies include: vehicle age (Green and Hu, 1984; Hensher, 1985; Hensher *et al.*, 1990; Golob *et al.*, 1996; Golob *et al.*, 1997; Linciano, 1997), operating costs (Train and Lohrer, 1983; Mannering and Winston, 1985; Hensher, 1985; Hensher *et al.*, 1990; de Jong, 1996; Golob *et al.*, 1996; Golob *et al.*, 1997; Walls, 1998), and the cost of fuel (Greene and Hu, 1984; Linciano, 1997; Walls, 1998). Hypotheses underlying these variables include the fact that as vehicles age they become less reliable and efficient due to technology improvements and are consequently driven less, and that vehicles with higher operating costs would be used less in order to reduce costs incurred by households. The later is also expected to hold for the price of fuel, notwithstanding the generally inelastic demand for gasoline, diesel, etc.

The set of explanatory variables in Table 1 reflect most of these concerns with the exception of fuel price. However, this is not considered a major limitation. For example, Linciano (1997: 450) argues "...the impact of changes in fuel prices on the individual transport behaviour is stronger only in the long term". Information on different fuel types and consumption, however, has been included. For passenger vehicles it is hypothesised that leaded and mixed-fuel vehicles (*LDF*) will have a negative coefficient, as these petrol types are more common among older vehicles. The variable *OTF* representing diesel, LPG and dual fuel is hypothesised to have a positive influence on usage. Schipper *et al.* (2000) argue that the annual driving distances of vehicles with these fuels are significantly higher than those for gasoline-fuelled vehicles. This positive relationship is also expected for the freight fuel variables *DSL* (diesel) and *OTF* (leaded, LPG, dual). Efficiency of operation is also reflected in part by the specification of the fuel consumption rate for both passenger and freight vehicles (*RTE*). The age of the passenger and freight vehicles is indicated by the year of initial registration (*YRR*) and year of manufacture (*YRM*) respectively. These variables would imply a higher and lower likelihood of usage due to lower and higher operating costs and positive and negative *ex ante* coefficients are hypothesised respectively.

Several other variables are included to reflect additional vehicle attributes that may affect usage. In terms of the type or class of vehicle, Golob *et al.* (1996), Golob *et al.* (1997) and Hensher (1985) included vehicle types in their respective studies. The results suggested that vehicles associated with higher usage included subcompact cars, sports cars, full size standard vans and compact and standard sports utility vehicles. In contrast, lower usage is generally associated with mid-size cars, standard trucks and minivans. These are consistent with Golob's *et al.* (1996) reasoning that vehicles with higher usage levels tend to be driven principally by males, younger persons and employed persons, whereas vehicles with lower usage levels are driven by females or as second household vehicles.

Likewise, Linciano (1997: 450) included engine size on the basis that "...households who purchased a powerful vehicle might need to travel more extensively than those who brought a small car" and Hensher (1985) and Hensher *et al.* (1990) included variables indicating vehicle weight and whether the vehicle is used for towing. The present freight analysis includes a dummy variable for trailer towed (*TLR*) in this respect. For passenger vehicles, dummy variables are used to identify vehicle types as *FVU* (4WD, vans, utilities), *TAX* (taxis) and *MOT* (motorcycles), with sedans and station wagons as the

control variable. Due to the nature of work performed by taxis, it is hypothesised that *TAX* is positively related to vehicle usage, while motorcycles (*MOT*) generally travel a lower number of kilometres and are therefore likely to be negatively related to usage.

The vehicle types for freight vehicles are *LTK* (light truck), *RGD* (rigid truck), *PMR* (prime mover) and *OTH* (other non-freight carrying), while the control group is freight-carrying passenger vehicles. Greene and Hu (1984), for example, also included a truck vehicle class, though it only included standard-sized pickup trucks, vans and recreational vehicles, rather than freight trucks. It is hypothesised vehicle usage (*VKT*) will have a positive coefficient when regressed against long-distance freight vehicles *PMR* and *RGD* and a negative relationship when regressed against *LTK* and *OTH* which tend to be used for shorter distance freight transport. Additional dimensions of vehicle attributes included are the number of cylinders (*CYL*) and engine capacity (*ENG*) for passenger vehicles and the number of axles (*AXL*) and gross combination mass (*GCM*) for freight vehicles. Vehicles with a greater cylinders, engine capacity or axles are expected to possess a higher vehicle power to weight ratio and are assumed to have a positive influence on vehicle usage. Lastly, a dummy variable reflecting an automatic transmission *TRN* is included for both passenger and freight vehicles. No particular sign is hypothesised when *VKT* is regressed against *TRN*.

The final set of explanatory variables included in Table 2 relate to purpose factors. These are intended to reflect the principal purposes and locations in which the vehicle is used. Information on the main area travelled by the vehicle is incorporated in both the passenger and freight vehicle models by the proportion of travel that is intrastate travel (outside of the capital city) (*INA*) and interstate (*INR*). While ABS (2001a) estimates indicate only a relatively small number of vehicles travel interstate, freight vehicles dominate this area of travel, and it could be logically assumed that the coefficient *INR* in the freight study will be positively related to usage. The distance that each vehicle travels for business purposes (*PBU*) or personal use (*PPU*) is included for passenger vehicles to reflect the differing requirements of work and recreational travel. The *ex ante* sign on *PBU* is thought to be negative. Lastly, specific information on the type and tonnage of commodities and the distances travelled for freight purposes are included for freight vehicles. Commodities carried are categorised into *ANF* (animal/food freight), *CMM* (chemicals/minerals/crude materials freight), *MFG* (manufactured goods freight), *MCH* (machinery/tools of trade freight), and *OCM* (other commodities freight). In Australia, the commodities in *CMM* represent the majority of freight carried by road vehicles, though *ANF* and *MFG* also represent significant proportions of freight transported. Two additional usage variables are included for freight vehicles. These are total tonnes carried (*TON*) and the distance travelled laden for business purposes (*LBU*). Estimates generally show that for the majority of kilometres travelled by freight vehicles they are laden for business use. Finally, estimates for freight vehicles also include information on whether the freight carried by the vehicle is owned personally or by a business (*OWN*). No particular signs are hypothesised when *VKT* is regressed on *TON*, *LBU* and *OWN*.

IV. EMPIRICAL RESULTS

The estimated coefficients and standard errors of the parameters for the passenger and freight vehicle parameters are presented in Tables 3 and 4 respectively. Care must be taken in interpreting estimated coefficients in these models. While a positive (negative) coefficient would indicate a shift in probability to the right-most (left-most) cell, the impacts on the middle cells are ambiguous and depend on the particular density functions. Also included in Tables 3 and 4 are statistics for joint hypothesis and likelihood ratio tests. The results of a prediction success table for the dependent variable for both the passenger and freight models are presented in Table 5. Five separate models are estimated for passenger and freight vehicles. The estimated coefficients and standard errors employing the entire set of driver, vehicle and purpose characteristics are shown in columns 1 and 2 of Tables 3 and 4. The results of estimations using first, the set of driver characteristics, then the set of vehicle attributes, and finally, the set of purpose factors alone, are detailed in columns 3 and 4, 5

and 6 and 7 and 8 respectively. Columns 9 and 10 contain the estimated coefficients and standard errors for a final specification.

<TABLE 3 HERE>

In terms of the passenger vehicle analysis in Table 3, all of the estimated models are highly significant, with likelihood ratio tests of the hypothesis that all of the slope coefficients are zero rejected at the .01 level of significance using the χ^2 statistic. It can then be concluded that each of these models have greater explanatory power than an intercept only model. The performance of the complete model can be partially assessed on the basis of the Pseudo R^2 value, defined as $1 - \ln L / \ln L(0)$, where $\ln L(0)$, is the value of the log-likelihood function when the only explanatory variable is the constant term and $\ln L$, is the maximised values of the log-likelihood function. This value indicates that 48.3 percent of the variation in the underlying scale of usage levels can be explained by the full specification. For the individual equations the Pseudo R^2 is highest for purpose factors at 43 percent, while the vehicle attribute and driver characteristic models are 18.6 percent and 2.2 percent respectively. This would suggest that purpose factors contribute a larger proportion of the information explaining vehicle usage levels.

However, despite the performance of the overall original specification less than half of the individual coefficients are significant at the .10 level. Of the significant coefficients *AGE*, *FVU*, *MOT*, *PPU*, *PBU* and *INA* are all significant at the .01 level, while *HSE*, *CYL*, *ENG* and *YRR* are significant at either the .05 or .10 levels of significance. Each of the signs on these estimated coefficients save *ENG* conform to *a priori* expectations. This would suggest that vehicles with older drivers (relative to younger drivers), that are a 4WD/van/utility or a motorcycle (relative to sedans/hatches/station wagons) and vehicles that travel intrastate (relative to vehicles that travel in the capital city only) are more likely to exhibit lower levels of usage, while younger vehicles in households with a larger number of drivers will have higher levels of usage. While the estimated coefficient for the number of cylinders (*CYL*) as a proxy for engine power is significant, the estimated sign on engine size (*ENG*) does not conform to a prior expectations. The estimated coefficients for *SEX*, *VIC*, *SA*, *QLD*, *WA*, *OTH*, *LDF*, *OTF*, *RTE*, *TRN*, *TAX* and *INR* are all insignificant.

These results are generally consistent with the estimated coefficients for the second, third and fourth regressions where only the sets of driver characteristics, vehicle attributes and purpose factors are included. In the second regression where only the driver characteristics are included the coefficient for the number of drivers in the household (*HSE*) is now significant, while driver's age (*AGE*) has become insignificant. These results together with the full specification suggest that State/Territory of registration and driver gender are not important determinants of vehicle usage. For the model solely estimating vehicle attributes, a number of the variables that appeared as significant in the complete model specification are now insignificant. These include, *ENG*, *CYL* and *FVU*, although other previously insignificant variables are now significant, such as, *LDF*, *OTF*, *RTE* and *TAX*. All of these significant coefficients conform to *a priori* expectations (where previously *TAX* did not). All other things being equal, late model vehicles using unleaded or diesel fuel that have lower rates of fuel consumption are associated with a higher rate of usage.

For the estimated coefficients from the third purpose factor model *PPU*, *PBU* and *INA* are still significant, while interstate vehicle travel *INR* is now significant at the .05 level. These results confirm further that purpose factors account for a significant amount of information in the passenger vehicle usage model. Log-likelihood tests are employed to reject the null hypotheses that the model of passenger vehicle usage could be estimated on the basis of the nested 'driver

characteristics', 'vehicle attributes' and 'purpose factors' models, and we may conclude that vehicle usage is a function of all three sets of variables.

In order to further refine the overall specification, Wald and LR tests were used to test combinations of coefficients for joint significance and on this basis a number of variables were excluded from the final specification. The final specification is presented in columns 9 and 10 of Table 3. The likelihood ratio for the final specification is significant at the .01 level. Coefficients in the final specification found to have an influence on vehicle usage are similar in sign and significance to those in the full specification. Driver age (*AGE*), the number of drivers in the household (*HSE*), the vehicle's engine capacity (*ENG*), the number of vehicle cylinders (*CYL*), whether the vehicle is a 4WD/van/utility (*FVU*) or motorcycle (*MOT*), is used mainly for personal use (*PPU*) or business use (*PBU*) and whether the vehicle travels intrastate (*INA*) all exhibit significant relationships and conformed with hypothesised expectations.

The results indicate, all other things being equal, that vehicles with older drivers (relative to younger drivers), or with high engine capacities, fwd/van/utility vehicles or motorcycles (relative to sedans/hatches/station wagons), and vehicles that mainly travel intrastate (relative to vehicles that only travel in the capital city) have a higher probability of travelling a lower number of kilometres and thus a lower probability of having a high level of usage. On the other hand, vehicles in households with a greater number of drivers, vehicles with a higher number of cylinders, and where vehicles are mainly used for business purposes have a greater probability of travelling a larger number of kilometres.

The estimated limit points in Table 3 identify the thresholds of usage for each category (very low, low, medium, high and very high). From the limit points of the revised regression model it can be concluded that there is not a significant amount of difference between vehicles that travel either a very low or low number of kilometres, low or medium number of kilometres or between vehicles that travel a medium or high number of kilometres. However, estimates of the fourth limit point, differentiating usage between those vehicles that travel a high or very high number of kilometres are significant at the .10 level. This indicates that vehicles that travel a high number of kilometres can be differentiated from those that incur very high usage levels.

Finally, the ability of the model to accurately predict usage for passenger vehicles is gauged on the basis of a prediction success table for the final specification. Table 5 contains the predicted and observed results. For example, of the 151 vehicles defined as very high usage, the final model specification predicted 146 (96.7%) correctly, and identified 5 vehicles (3.3%) incorrectly. Alternatively, when used to predict a medium level of usage, 126 (84.0%) instances were correctly identified and 24 cases (16.0%) incorrectly, while 97.4% of very low vehicle usage was identified correctly. These findings would suggest that the model of vehicle usage employed might be more useful in identifying very high and very low vehicle usage rather than a medium level of usage. Nonetheless, the final specification correctly identified 91.2 percent of vehicles correctly as very low, low, medium, high or very high usage based on the set of explanatory variables employed.

The estimated coefficients and standard errors for the freight vehicle models are presented in Table 4. Similarly to the passenger vehicle analysis, the full specification comprising the full vector of driver, vehicle and purpose variables are displayed in columns 1 and 2. The results from the models estimating solely the influence of the driver characteristics, vehicle attributes and purpose factors are presented in columns 3 and 4, 5 and 6, and 7 and 8 respectively. The estimated coefficients and standard errors of a revised freight usage model are shown in columns 9 and 10.

<TABLE 4 HERE>

The likelihood ratio test statistics for all of these models are significant at the .01 level, thereby rejecting the null hypothesis that all of the slope coefficients are jointly zero. The Pseudo R^2 value of the full specification is also significant indicating that approximately 69.7 percent of the variation in the underlying freight vehicle usage model can be explained by the full set of explanatory variables. The Pseudo R^2 values of the individual characteristics models also provide an indication of those sets of variables that have relatively greater explanatory power in the complete model. For example, the driver characteristics and vehicle attribute models alone account for only 0.9 percent and 24.1 percent of the variation in usage respectively, while information concerning vehicle purpose accounts for 65.4 percent of variation in the full model.

While the overall performance of the full specification is sound, a number of the estimated coefficients are not significant. The coefficients that are significant at the .01 level are *SEX*, *LTk*, *RGD*, *PMR*, *OTH*, *YRM*, *PBU* and *LBU*; *WA* and *INR* are significant at the .05 level, and *HSE* is significant at the .10 level. However, only the signs on *LTk*, *OTH*, *YRM*, *INR* and *PBU* conform with *a priori* expectations. Therefore, it could be concluded that light trucks (*LTk*) and other non-freight carrying vehicles (*OTH*) (relative to passenger vehicles) have a higher probability of exhibiting lower usage patterns, while newer freight vehicles (*YRM*), vehicles that travel intrastate (*INR*) (relative to vehicles that only travel in the capital city).

Additional models are again estimated separately on the basis of driver characteristics, vehicle attributes and purpose factors. The results of the regression including only driver characteristics show a slight difference in the estimated outcomes of some coefficients. For example, *AGE* is now significant at the .01 level, while *HSE* and *OTH* are now significant at the .05 level. Further, *WA*, which was significant in the original model, is no longer. Most surprising is that driver age (*AGE*), number of household drivers (*HSE*) and driver gender (*SEX*) now all have the correct sign. Of the insignificant coefficients, all variables display the correct sign, except for *QLD* for which the sign has changed directions. Similar to the passenger vehicle results, this would indicate that the states/territory of registration exhibits little influence on vehicle usage levels.

The estimated coefficients from the vehicle attributes regression displays very different results from those in the original model. For example, while the variables *PMR* and *OTH* still remain significant, the coefficient estimates for *LTk* and *RGD* are now insignificant. Further to this, the previously insignificant variables *OTF*, *GCM*, *OWN* and *AXL* are now identified as having a significant influence at the .01 level, while *TLR* is significant at the .05 level. In addition all of the significant variables are displaying the hypothesised sign, except for information on other vehicle types (*OTH*), which has changed signs. The result concerning freight vehicle purpose factors has not changed significantly from the full specification. Interstate travel (*INR*) and business usage (*PBU*) have remained as significant determinants of usage levels, however, distance travelled laden (*LBU*) is no longer significant, even at the .10 level. The majority of the signs of the estimated coefficients have remained the same, the exception being *INA*. While none of the commodity coefficients are significant, purpose factors still represent an important component of vehicle usage levels. From the log-likelihood estimates for each of these models, the null hypotheses that the nested models alone can determine vehicle usage levels are rejected and it can be concluded that freight vehicle usage is a function of driver characteristics, vehicle attributes and purpose factors.

Redundant variable tests are again undertaken so as to refine the full specification. Using the log-likelihood ratio statistic, the hypothesis that the coefficients of the group of variables are jointly zero determines whether the variables can be excluded from the final specification. The driver characteristics group (*AGE*, *HSE* and *SEX*) is determined to be significant at the .01 level and retained in the revised model. However, the States/Territories group (*VIC*, *QLD*, *SA*, *WA* and *OTH*) fails to be significant and is dropped from the final specification. Three groups of vehicle characteristics were tested for redundancy, these being, fuel type (*DSL* and *OTF*), vehicle type

(*LTK*, *RGD*, *PMR* and *OTH*), and other characteristics (*GCM*, *OWN*, *RTE*, *TLR*, *TRN*, *YR* and *AXL*). The vehicle type group was considered highly significant, justifying the inclusion of these variables in the model. The other vehicle characteristics group of variables was also significant, albeit at the .05 level, and also included in the final specification. The grouping of fuel types fails redundancy and is excluded from the refined specification. The final redundant variables tests were conducted on the vehicle usage characteristics categorised as area travelled (*INA* and *INR*), commodities carried (*ANF*, *CMM*, *MFG*, *MCH* and *OTH*), and business use (*PBU*, *LBU* and *TON*). Of these vehicle usage groupings those that failed to be excluded from the final specification include the business use (.01 level) and the area travelled variables (.10 level).

The estimated coefficients and standard errors of the refined or final specification are included in columns 9 and 10 of Table 5.3. The log-likelihood ratio statistic indicates that at the .01 level, the explanatory variables are significant indicators of the levels of freight vehicle usage in Australia. A test was also performed to compare the performance of the refined specification to those included in the original specification to determine whether the model could be estimated on the basis of the smaller set of variables. The test statistic of 11.6538 calculated from the log-likelihood estimates is compared with the critical χ^2 value at the .05 level of significance with the degrees of freedom equal to the difference in the number of variables from the full and refined specifications. From the test statistic it can be concluded that freight vehicle usage can be estimated on the basis of the smaller refined specification. However, the Pseudo R^2 is slightly lower at 69.5 percent in the refined specification.

<TABLE 5 HERE>

The estimated coefficients from the refined specification do not appear to have changed significantly from the results generated earlier. The number of drivers (*HSE*), light trucks (*LTK*), rigid trucks (*RGD*), prime movers (*PMR*), other vehicle types (*OTH*) and distance laden for business use (*LBU*) have all been estimated as having a significantly negative influence on the level of vehicle usage. Those significant variables determined as having a positive influence include driver's sex (*SEX*), year of manufacture (*YRM*), interstate travel (*INR*) and distance travelled for business use (*PBU*). All other things being equal, female drivers (relative to male drivers), newer vehicles, vehicles that mainly travel interstate (compared with vehicles that travel in the capital city only) and vehicles that are mainly used for business purposes have a higher probability of exhibiting higher usage patterns. By comparison, vehicles with a greater number of drivers, light trucks, rigid trucks, prime movers, other vehicle types (all vehicle types relative to passenger vehicles) and the distance travelled laden for business use have a greater probability of lower usage.

The thresholds of usage for each category (very low, low, medium, high and very high) have also been estimated and are represented by the limit points in Table 4. As each of these limit points in the revised model are significant at the .01 percent level, it indicates that there is an identifiable difference between freight vehicles that travel in each category of usage. Lastly, the predictive ability of the final specification is assayed in Table 5. Overall, the model correctly predicted the usage of 96.4 percent of observed cases. The model was most accurate for predicting high and very high levels of usage with 98.7 and 100.0 percent correctly predicted in these instance respectively. Predictions were generally less accurate for very low (92.4 percent) and medium (94.7 percent) levels of usage.

V. CONCLUDING REMARKS

The present study uses a multinomial ordered probit model to investigate the driver characteristics, vehicle attributes and purpose of travel as determinants of motor vehicle usage in Australia. Separate models were estimated for passenger and freight vehicles. The current paper extends empirical work in this area in at least two ways. First, and as far as the authors are aware, it represents the first attempt to apply qualitative statistical models of vehicle usage to the unit record files underlying the Australian Bureau of Statistics Survey of Motor Vehicle Usage. Second, the study analyses in detail the varying influences of driver characteristics, vehicle attributes and purpose factors on vehicle usage as defined by vehicle kilometres travelled. The results indicate that a large number of factors are likely to impact upon usage for both passenger and freight vehicles. For passenger vehicles, the age of the principal driver, the number of drivers in the household, engine characteristics such as size and the number of cylinders, the amount of travel outside of capital cities and interstate and the level of business-related travel are significant determinants of usage. For freight vehicles, the number of drivers, whether the principal driver is female, vehicle type and the year of manufacture are significantly related to vehicle kilometres travelled.

Of course, the study does suffer a number of limitations, all of which suggest directions for future research. First, one particular problem with the data set employed is the lack of attention given to socio-economic variables. This is not uncommon in work of this type. Mannering (1983: 187), for example, also noted that his research could have been enhanced by the inclusion of more detailed data, "...specifically information relating to the type of activities the principal driver actually undertakes, such as type of work, types of leisure activities [etc]". A wider variety of driver-related characteristics may enhance our understanding of vehicle usage. Second, the cross-sectional data used in the study incorporates information on vehicle usage collected over a 13 week time period. While this relatively short time period allows some potential determinants of usage to be assumed constant, such a short time period also means that seasonal variation in usage is unable to be considered. Unfortunately, the ABS survey is not conducted in a manner that would permit cases to be linked across different collection periods.

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TABLE 1. *Categories of distances travelled for passenger and freight vehicles*

Category	Passenger vehicles		Freight vehicles	
	Lower bound	Upper bound	Lower bound	Upper bound
Very Low Usage	1.022	980.042	3.765	1,673.250
Low Usage	980.681	2,111.054	1,677.282	4,404.717
Medium Usage	2,119.000	3,631.738	4,415.129	8,432.612
High Usage	3,632.789	6,223.676	8,445.393	20,943.220
Very High Usage	6,231.231	59,452.130	21,087.000	128,850.000

TABLE 2. *Selected descriptive statistics for passenger and freight vehicles*

Vehicle	Description	Code	Mean	Standard deviation	Kurtosis	Skewness	
Passenger vehicles	Driver characteristics	Kilometres travelled	VKT	6314.340	10269.381	7.405	2.790
		Age of principal driver	AGE	43.966	14.177	-0.380	0.349
		Number of vehicle drivers	HSE	1.408	0.638	6.364	2.013
		Sex of principal driver	SEX	0.305	0.461	-1.279	0.851
		Victoria	VIC	0.164	0.370	1.326	1.823
		Queensland	QLD	0.129	0.335	2.928	2.218
		Western Australia	WA	0.104	0.305	4.797	2.605
		South Australia	SA	0.128	0.334	3.008	2.236
		Other states	OTH	0.305	0.461	-1.279	0.851
	Vehicle attributes	Leaded & mixed petrol	LDF	0.165	0.371	1.278	1.810
		Other fuels – diesel, LPG, duel	OTF	0.186	0.390	0.612	1.616
		Engine capacity	ENG	2405.963	1300.197	-0.920	0.182
		Fuel consumption rate	RTE	11.680	5.024	1.047	0.965
		Vehicle Transmission	TRN	0.501	0.500	-2.005	-0.005
		Year of registration	YRR	1991.336	6.367	5.108	-1.604
		Number of cylinders	CYL	4.532	1.577	0.506	-0.169
		4WD/van/utility	FVU	0.116	0.320	3.808	2.408
		Taxi	TAX	0.149	0.356	1.910	1.976
	Motorcycle	MOT	0.176	0.381	0.924	1.709	
	Purpose factors	Intrastate area travelled	INA	0.379	0.485	-1.755	0.500
		Intrastate area travelled	INR	0.049	0.216	15.487	4.177
		Distance travelled for business use	PBU	4183.620	10739.098	7.769	2.919
		Distance travelled for personal use	PPU	1417.479	1868.613	20.795	3.333
Freight vehicles	Driver characteristics	Age of principal driver	AGE	42.905	10.939	0.493	0.408
		Number of vehicle drivers	HSE	1.529	0.927	4.234	2.096
		Sex of principal driver	SEX	0.021	0.144	42.537	6.670
		Victoria	VIC	0.170	0.376	1.081	1.755
		Queensland	QLD	0.150	0.357	1.860	1.964
		Western Australia	WA	0.107	0.309	4.520	2.553
		South Australia	SA	0.138	0.345	2.406	2.099
		Other states	OTH	0.253	0.435	-0.710	1.136
		Vehicle attributes	Diesel fuel	DSL	0.768	0.422	-0.378
	Other fuels – leaded, LPG, duel		OTF	0.093	0.290	5.894	2.808
	Light truck		LTK	0.066	0.248	10.269	3.501
	2, 3 or 4 axle rigid truck		RGD	0.313	0.464	-1.352	0.806
	2, 3 or 4 axle prime mover		PMR	0.294	0.456	-1.185	0.903
	Other non-freight carrying		OTH	0.068	0.251	9.914	3.450
	Gross combination mass of vehicle		GCM	21142.025	23399.601	5.319	1.933
	Fuel consumption rate		RTE	31.049	19.389	0.559	0.978
	Trailer towed		TLR	0.333	0.472	-1.501	0.708
	Transmission		TRN	0.074	0.262	8.553	3.247
	Year of manufacture		YRM	1990.264	7.114	2.046	-1.177
	Number of axles		AXL	2.239	0.785	2.160	-1.111
	Purpose factors	Intrastate area travelled	INA	0.525	0.500	-1.992	-0.099
		Interstate area travelled	INR	0.105	0.307	4.660	2.580
		Freight ownership – own/other	OWN	0.340	0.474	-1.542	0.678
		Animal/food freight	ANF	236.180	964.569	62.096	7.035
		Chemical/minerals/crude materials freight	CMM	654.532	2731.328	100.655	8.198
		Manufactured goods freight	MFG	197.875	929.910	76.497	7.870
		Machinery/tools of trade freight	MCH	92.473	661.873	634.482	21.407
		Other commodities freight	OCM	111.416	615.440	194.991	11.678
		Distance travelled for business use	PBU	12786.369	17980.647	5.555	2.211
		Distance travelled laden	LBU	9017.481	14542.168	8.940	2.761
		Total tonnes carried	TON	1292.812	3090.430	58.735	5.895

Notes: Passenger vehicle dummy variable controls: sex–male, state registration–NSW, fuel–unleaded petrol, transmission–manual, vehicle type–sedans/hatches/station wagons, and area travelled–capital city only. Freight vehicle dummy variable controls: sex–male, state registration–NSW, fuel–unleaded petrol, vehicle type–passenger vehicles (sedans/hatches/station wagons/vans/4WD/utilities), trailer towed–no trailer, transmission–manual, area travelled–capital city only, and freight ownership–own.

TABLE 3. *Multinomial ranked probit model maximum-likelihood estimates for passenger vehicles*

	Full specification		Driver characteristics only		Vehicle attributes only		Purpose factors only		Final specification	
	Estimated coefficient	Standard error	Estimated coefficient	Standard error	Estimated coefficient	Standard error	Estimated coefficient	Standard error	Estimated coefficient	Standard error
AGE	*** -0.0187	0.0035	-0.0026	0.0029	—	—	—	—	*** -0.0188	0.0035
HSE	** 0.1813	0.0819	*** 0.4345	0.0637	—	—	—	—	** 0.1753	0.0812
SEX	-0.1563	-1.4376	-0.1282	0.0852	—	—	—	—	-0.1529	0.1077
VIC	0.1845	0.1572	0.0861	0.1336	—	—	—	—	—	—
QLD	-0.0211	0.1716	0.1292	0.1424	—	—	—	—	—	—
WA	0.0011	0.1808	0.0417	0.1516	—	—	—	—	—	—
SA	-0.0763	0.1720	-0.1183	0.1433	—	—	—	—	—	—
OTH	0.1264	0.1384	0.0502	0.1164	—	—	—	—	—	—
LDF	0.2446	0.1620	—	—	*** 0.4863	0.1465	—	—	—	—
OTF	0.2368	0.2045	—	—	** 0.3736	0.1659	—	—	—	—
ENG	* -0.0002	0.0001	—	—	-0.0000	0.0001	—	—	* -0.0002	0.0001
RTE	-0.0199	0.0143	—	—	** -0.0292	0.0124	—	—	-0.0164	0.0141
TRN	-0.1202	0.1183	—	—	0.0293	0.1019	—	—	-0.1390	0.1163
YRR	* 0.0194	0.0101	—	—	*** 0.0664	0.0089	—	—	0.0117	0.0078
CYL	** 0.1418	0.0684	—	—	0.0964	0.0625	—	—	** 0.1361	0.0677
FVU	*** -0.6035	0.1824	—	—	-0.1418	0.1535	—	—	*** -0.5189	0.1690
TAX	-0.3487	0.2699	—	—	*** 1.3982	0.1884	—	—	-0.2711	0.2515
MOT	*** -1.4046	0.1909	—	—	*** -1.7029	0.1629	—	—	*** -1.3131	0.1841
PPU	*** 0.0008	0.0001	—	—	—	—	*** 0.0008	0.0000	*** 0.0008	0.0000
PBU	*** 0.0008	0.0001	—	—	—	—	*** 0.0008	0.0001	*** 0.0008	0.0001
INA	*** -0.3317	0.1008	—	—	—	—	*** -0.3974	0.0947	*** -0.3348	0.0994
INR	-0.2001	0.2098	—	—	—	—	** -0.4319	0.1968	-0.1899	0.2069
<i>lnL</i>	-626.1460	—	-1184.202	—	-984.7642	—	-689.3053	—	-629.6309	—
<i>lnL</i> (0)	-1210.293	—	-1210.293	—	-1210.293	—	-1210.293	—	-1210.293	—
<i>LR</i>	*** 1168.295	—	*** 52.1818	—	*** 451.0583	—	*** 1041.976	—	*** 1161.325	—
<i>P</i> (2)	* 37.5454	20.1141	** -0.3839	0.1888	*** 131.0914	17.8277	0.0728	0.0856	22.1281	15.6059
<i>P</i> (3)	* 38.7948	20.1196	0.2313	0.1888	*** 131.9045	17.8337	*** 1.1303	0.0911	23.3670	15.6105
<i>P</i> (4)	** 39.9993	20.1194	*** 0.7643	0.1900	*** 132.5715	17.8369	*** 2.1830	0.1096	24.5546	15.6100
<i>P</i> (5)	** 42.0349	20.1168	*** 1.3697	0.1924	*** 133.4013	17.8412	*** 4.1401	0.1900	* 26.5851	15.6070

Notes: *lnL* – log-likelihood, *lnL*(0) – restricted slopes log-likelihood, *LR* – likelihood ratio statistic; *P*(*n*) – category cut-off points. Asterisks denote significance at the: *** – .01 level, ** – .05 level and * – .10 level.

TABLE 4. *Multinomial ranked probit model maximum-likelihood estimates for freight vehicles*

	Full specification		Driver characteristics only		Vehicle attributes only		Purpose factors only		Final specification	
	Estimated coefficient	Standard error	Estimated coefficient	Standard error	Estimated coefficient	Standard error	Estimated coefficient	Standard error	Estimated coefficient	Standard error
AGE	-0.0044	0.0031	***-0.0106	0.0022	—	—	—	—	-0.0042	0.0030
HSE	*-0.0703	0.0401	**0.0672	0.0264	—	—	—	—	*0.0719	0.0396
SEX	***0.8173	0.1923	***-0.5552	0.1681	—	—	—	—	***0.8150	0.1902
VIC	0.1649	0.1220	0.0862	0.0820	—	—	—	—	—	—
QLD	0.0032	0.1219	-0.0319	0.0846	—	—	—	—	—	—
WA	**0.2889	0.1291	-0.1339	0.0937	—	—	—	—	—	—
SA	-0.0581	0.1353	-0.0983	0.0869	—	—	—	—	—	—
SOT	0.0739	0.1056	** -0.1733	0.0745	—	—	—	—	—	—
DSL	-0.1265	0.1219	—	—	0.0072	0.1016	—	—	—	—
OTF	-0.0698	0.1450	—	—	***0.4600	0.1204	—	—	—	—
LTK	***-0.7515	0.1514	—	—	-0.0944	0.1232	—	—	***-0.8045	0.1369
RGD	***-0.8516	0.1322	—	—	0.0973	0.1009	—	—	***-0.9262	0.1080
PMR	***-0.9925	0.2642	—	—	**0.3991	0.1735	—	—	***-1.0393	0.2471
OTH	***-1.1828	0.3551	—	—	*0.4175	0.2273	—	—	***-1.2417	0.3425
GCM	-0.0000	0.0000	—	—	***0.0000	0.0000	—	—	-0.0000	0.0000
OWN	0.0798	0.1043	—	—	***0.7544	0.0673	—	—	0.0672	0.1025
RTE	0.0006	0.0042	—	—	-0.0015	0.0029	—	—	0.0010	0.0041
TLR	0.1984	0.1628	—	—	**0.2993	0.1192	—	—	0.1740	0.1602
TRN	0.0446	0.1278	—	—	-0.0959	0.1038	—	—	0.0832	0.1231
YRM	***0.0233	0.0064	—	—	***0.0917	0.0047	—	—	***0.0231	0.0056
AXL	0.0210	0.1368	—	—	***0.2623	0.0854	—	—	0.0170	0.1338
INA	0.0179	0.0749	—	—	—	—	-0.0494	0.0683	-0.0015	0.0730
INR	**0.3952	0.1706	—	—	—	—	**0.3184	0.1600	***0.3416	0.1668
PBU	***0.0006	0.0000	—	—	—	—	***0.0005	0.0000	***0.0006	0.0000
ANF	0.0018	0.0050	—	—	—	—	0.0043	0.0078	—	—
CMM	0.0018	0.0050	—	—	—	—	0.0043	0.0078	—	—
MFG	0.0018	0.0050	—	—	—	—	0.0042	0.0078	—	—
MCH	0.0019	0.0050	—	—	—	—	0.0043	0.0078	—	—
OTH	0.0019	0.0050	—	—	—	—	0.0043	0.0078	—	—
TON	-0.0018	0.0050	—	—	—	—	-0.0043	0.0078	0.0000	0.0000
LBU	***0.0001	0.0000	—	—	—	—	0.0000	0.0000	***-0.0001	0.0000
<i>lnL</i>	-923.3997	—	-3023.036	—	-2317.608	—	-1054.910	—	-929.2266	—
<i>lnL(0)</i>	-3049.882	—	-3049.882	—	-3051.493	—	-3051.493	—	-3049.882	—
<i>LR</i>	***4252.965	—	***53.6918	—	***1467.771	—	***3993.167	—	***4241.311	—
<i>P(2)</i>	***46.2089	12.8083	***-1.2769	0.1241	***182.5933	9.4148	***0.5417	0.0670	***45.7342	11.1709
<i>P(3)</i>	***47.9690	12.8138	***-0.6797	0.1221	***183.4122	9.4200	***2.0350	0.0811	***47.4832	11.1778
<i>P(4)</i>	***50.3484	12.8182	***-0.1636	0.1214	***184.1966	9.4251	***4.1531	0.1273	***49.8427	11.1815
<i>P(5)</i>	***58.1864	12.8089	***0.4329	0.1221	***185.2658	9.4326	***11.1268	0.3646	***1.0050	11.1685

Notes: *lnL* – log-likelihood, *lnL(0)* – restricted slopes log-likelihood, *LR* – likelihood ratio statistic; *P(n)* – category cut-off points. Asterisks denote significance at the: *** – .01 level, ** – .05 level and * – .10 level.

TABLE 5. *Observed and predicted values for passenger and freight vehicles*

Type	Usage category	Observed observations	Predicted observations	Percent correct
Passenger	Very Low Usage	151	147	97.4%
	Low Usage	150	177	82.0%
	Medium Usage	150	126	84.0%
	High Usage	150	156	96.0%
	Very High Usage	151	146	96.7%
Freight	Very Low Usage	380	409	92.4%
	Low Usage	379	365	96.3%
	Medium Usage	379	359	94.7%
	High Usage	378	383	98.7%
	Very High Usage	379	379	100.0%